Artificial Neural Network Modeling for Improved On-Wafer OSLT Calibration Standards

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ABSTRACT: We apply artificial neural networks (ANNs) to improve the modeling of on-wafer open-short-load-thru (OSLT) standards used for calibrating vector network analyzers. The ANNs are trained with measurement data obtained from a benchmark multiline thru-reflect-line (TRL) calibration. We assess the accuracy of an OSLT calibration using these ANN-modeled standards, and find that it compares favorably (less than a 0.02 difference in magnitude) to the benchmark multiline TRL calibration over a 40 GHz bandwidth. We also quantify the training errors and training times as a function of both the number of training points and the number of neurons in the hidden layer. © 2000 John Wiley & Sons, Inc. Int J RF and Microwave CAE 10: 319–328, 2000.

Keywords: artificial neural network; network analyzer; calibration model; standards

I. INTRODUCTION

The open-short-load-thru (OSLT) calibration [1] is one of the most widely used techniques for calibrating vector network analyzers (VNAs). It is mainly used with devices that contain coaxial or waveguide interfaces, but is also often applied to on-wafer environments such as microstrips and coplanar waveguide (CPWs). The calibration procedure consists of a "thru" connection of the two VNA ports, as well as the measurement (on both ports) of three one-port standards, typically a nominal open, a nominal short, and a nominally matched load. None of these standards needs to be ideal, but we must know their reflection coefficients. In practice, our definition of these reflection coefficient values is typically drawn from a model of the standard.

Manufacturers of calibration kits usually provide a description of the standards based on equivalent circuit parameters, known as calibration kit parameters [2, 3] or calibration component coefficients [4]. These parameters assume single, real values for both load impedance and characteristic impedance, and describe the open- and short-circuit terminations as frequency polynomials of capacitance and inductance, respectively. With coaxial and waveguide standards, the equivalent circuit approximations have worked to the satisfaction of most users, but for on-wafer standards, a recent study [5] reported errors in scattering parameters of up to 0.5. Considering that the maximum possible value for passive devices is a magnitude of 1, such errors are clearly unacceptable. DeGroot et al. [6] recently addressed this issue by developing a general description of transmission lines to express offset reflection standards and finite-length thru standards that accounts for lossy environments with complex impedance. Implementing this general description, however, still requires physical models

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or measurement data of each for the individual standards.

With these encumbrances in mind, we have implemented a technique involving artificial neural networks (ANNs) to model OSLT calibration standards. This approach allows us to develop compact descriptions of the standards without having to formulate detailed physical models. These ANN descriptions have a number of advantages over using calibrated measurement data files, namely, they are more compact and less susceptible to noise inherent in measured data, and they can model the standards more accurately at interpolated frequencies, especially for sparse data sets.

The following sections describe our implementation of ANNs to model the on-wafer OSLT standards, although these methods can just as easily be used for any lumped-element calibration standards on any variety of substrates, such as alumina and Duroid. We quantify the training errors as a function of training points and the number of neurons in the hidden layer, and assess the accuracy of the OSLT calibration using these ANN-modeled standards. Through various comparisons, we show that ANN models offer several advantages over calibrated measurement data files.

II. ARTIFICIAL NEURAL NETWORKS

ANNs have been applied to diverse areas such as speech and pattern recognition, financial and economic forecasting, telecommunications, and nuclear power plant diagnosis, and have just recently been introduced into the area of microwave engineering [7–10]. In particular, researchers have successfully used ANNs to model microstrip vias [11], packaging and interconnects [12], spiral inductors [13], MESFET devices [14], CPW circuit components [15], the effective dielectric constant of microstrip lines [16], and HBT amplifiers [17], to name just a few.

The ANN architecture used in this work is a feedforward, three-layer perceptron structure (MLP3) consisting of an input layer, a hidden layer, and an output layer, as shown in Figure 1. The hidden layer allows complex models of input–output relationships. The mapping of these relationships is given by [11]

$$\mathbf{Y} = g[\mathbf{W}_2 \cdot g(\mathbf{W}_1 \cdot \mathbf{X})]$$

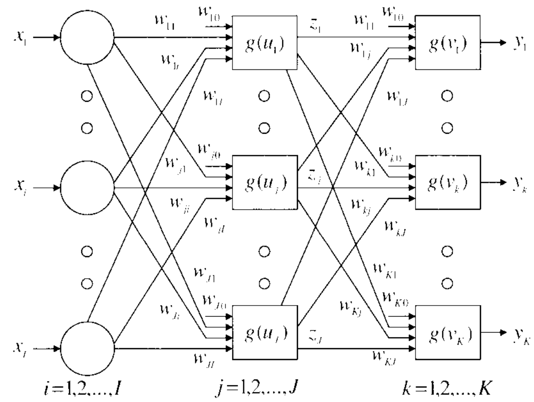

Figure 1. Artificial neural network architecture.

where $\mathbf{X}$ is the input vector, $\mathbf{Y}$ is the output vector, and $\mathbf{W}_1$ and $\mathbf{W}_2$ are the weight matrices between the input and hidden layers and between the hidden and output layers, respectively. The function $g(u)$ is a nonlinear sigmoidal activation function given by

$$g(u) = \frac{1}{1 + \exp(-u)}$$

where u is the input to a hidden neuron. According to [10], an MLP3 with one hidden sigmoidal layer is able to model almost any physical function accurately, provided that a sufficient number of hidden neurons are available.

ANNs learn relationships among sets of input–output data which are characteristic of the device or system under consideration. After the input vectors are presented to the input neurons and the output vectors are computed, the ANN outputs are compared to the desired outputs, and errors are calculated. Error derivatives are then calculated and summed for each weight until all of the training sets have been presented to the network. The error derivatives are used to update the weights for the neurons, and training continues until the errors reach prescribed values.

III. METHODOLOGY

Although multiple inputs and outputs are possible with this ANN architecture, we made use of one input parameter (frequency) and two output parameters (the real and imaginary components) for each measured scattering parameter. Since we measure reflection coefficients for three terminations at both ports and all four scattering parameters of the thru connection, we end up with ten ANN models. In this study, we utilized software developed by Zhang et al. [18] to construct our ANN models.

To model the on-wafer OSLT standards, we trained the ANNs with measurement data obtained from a benchmark multiline TRL calibration carried out with the NIST MultiCal software [19]. Multiline TRL is a highly accurate means of VNA calibration and is especially useful for on-wafer environments since the characteristic impedance can easily be calculated from dimensional measurements of the standards, which simply consist of a number of transmission lines of varying line lengths and a highly reflective termination. The disadvantage of this calibration method is that it requires a large amount of real estate on the wafer, due to the numerous long lines required for an accurate calibration. This is why compact calibration kits, such as OSLT, are usually preferred for on-wafer applications. The tradeoff is that the kits with smaller, lumped-element artifacts tend to be less accurate since it is more difficult to calculate the reflection coefficients of the standards. But if the compact calibration kits can be characterized using a benchmark calibration, such as multiline TRL, and they can be reproduced on other wafers with little variation, it is possible to perform an accurate on-wafer OSLT calibration.

Once the OSLT standards are characterized, the dilemma is whether to develop a model for each of the standards or to directly use the measurement data obtained from the benchmark calibration. We will show that ANN models allow us to develop compact descriptions of the standards without having to formulate detailed physical models, and that these ANN descriptions have a number of advantages over large, calibrated measurement data files.

A. Modeling the Standards

In this study, the OSLT and multiline TRL standards and devices were constructed of a CPW transmission line fabricated from 1.5 μm gold conductors evaporated on 500 μm thick semi-insulating GaAs [20]; the gold center conductor was 73 μm wide, and separated from the ground plane by 49 μm gaps. The five-line standards included a 0.55 mm thru line and four additional lines that were 2.135, 3.2, 6.565, and 19.695 mm longer. All of the standards were measured using on-wafer probes. The OSLT open circuit was defined by lifting the probe heads off the wafer, as recommended by probe manufacturers. For each standard, we measured scattering parameters at 192 frequencies from 0.5 to 40 GHz.

Once the OSLT standards had been characterized using a multiline TRL calibration, we determined how many neurons in the hidden layer were required to develop accurate ANN models. Our first experiment was to vary the number of neurons in the hidden layer for each of the standards. We started with one hidden neuron, noting the training error reported by the software after training was completed, and repeated this process while incrementing the number of hidden neurons until we reached a total of ten neurons. We performed this experiment on each of the standards using all 192 measured frequencies as training data. Figure 2 illustrates the results for S_{11} of the open, short, and load, and for S_{21} of the thru. Each of the standards had different errors, but no discernible improvements could be seen for more than five neurons. We also measured the training time for each standard while varying the number of hidden neurons, and found that the training time varied linearly with the number of hidden neurons. One hidden neuron required approximately 2 s of training time on the computer used, while ten hidden neurons required about 20 s of training time. These training times undoubtedly vary, depending on the speed of the computer, but the values give a relative idea of how much time is required per hidden neuron.

After we decided that five hidden neurons were sufficient, we studied how many training points were required to accurately model each standard. We trained each standard using all 192 points, and then tried smaller subsets of the measurement points, namely, 3, 5, 9, and 41 points. After the models for each of the standards were trained for the five sets of data, we compared them to the measurement data. To our surprise, we found that we could achieve good accuracy with as few as nine training points, and that as few as five training points were adequate for the open and short. Figures 3 and 4 show the magnitudes of the vector differences of S_{11} ($|\Delta S_{11}|$) between the measured data and the ANN models for various numbers of training points for the open and load standards, respectively. From these two plots, we see that the ANN model of the open standard agrees with measurement data to within 0.015 using as few as five training points. And the ANN model of the load standard agrees with measure-

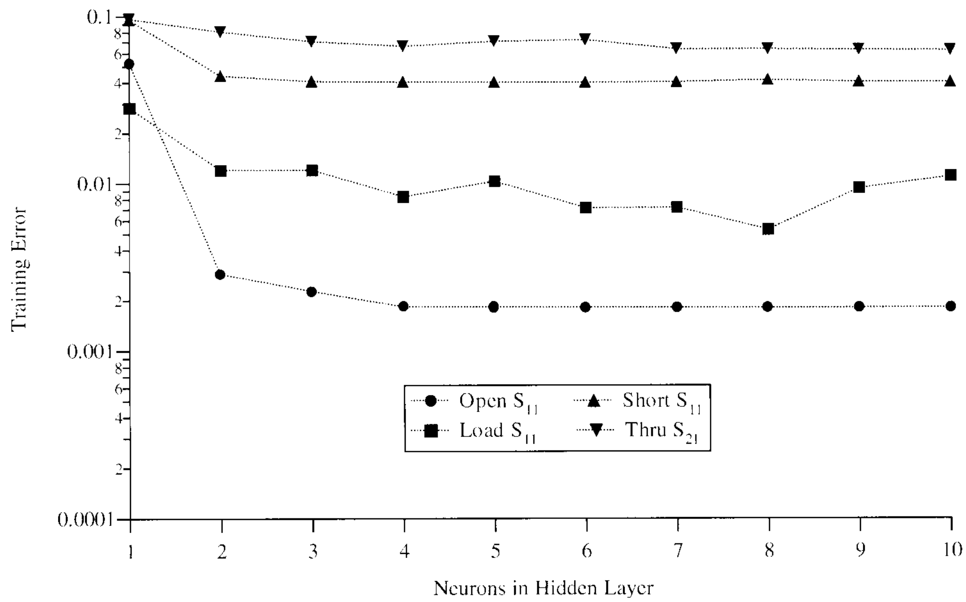

Figure 2. Training error versus the number of neurons in the hidden layer for various calibration standards.

ment data to within 0.04 for most frequencies using as few as nine training points.

Our observation that so few training points are sufficient to model our standards highlights an important advantage in using ANN models over calibrated measurement data files. We found that it is possible to cut down on calibration times by measuring only a few frequency points and developing an ANN model, rather than measuring numerous points and carrying around large data files. The ANN model, trained on only a few measurement points, can be much more accurate than linearly interpolating, as is commonly done in practice. For example, if one were to measure the load standard at five points and perform linear interpolation between frequencies, as shown in Figure 5, the maximum error would be 0.045, as opposed to only 0.016 for the ANN model trained using the same five points.

Next, we developed ANN models for each of the OSLT standards using five hidden neurons and all 192 measured points since we already had

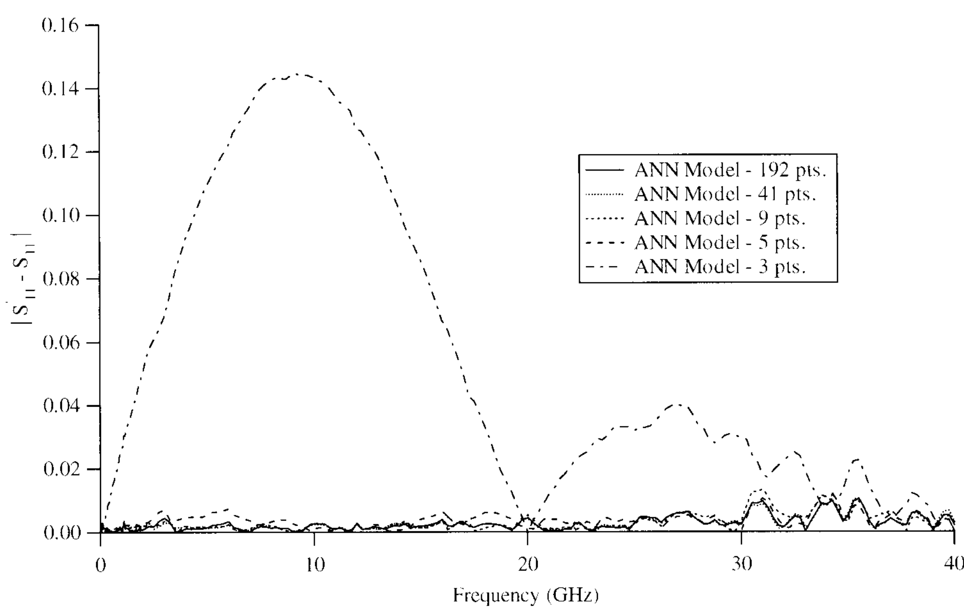

Figure 3. Magnitude of the ANN-modeled reflection coefficient errors ($|\Delta S_{11}|$) for the open standard with varying numbers of training points.

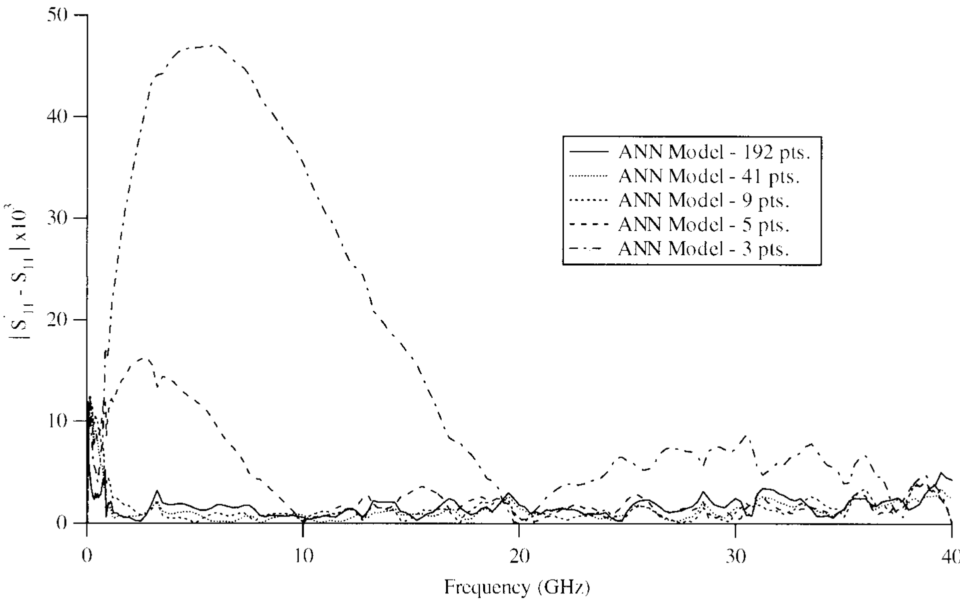

Figure 4. Magnitude of the ANN-modeled reflection coefficient errors ($|S\Delta_{11}|$) for the load standard with varying numbers of training points.

the data on hand. Figures 6–8 show the magnitude and phase of S_{11} using both measured and ANN model data for the open, short, and load standards, respectively. Figure 9 shows the magnitude and phase of S_{21} using the measured and ANN model data for the thru standard. Notice that the ANN models for each standard follow the trends of the measured data, but avoid the scatter of multiline TRL calibrated measurements. Whether or not this scatter is real, we see

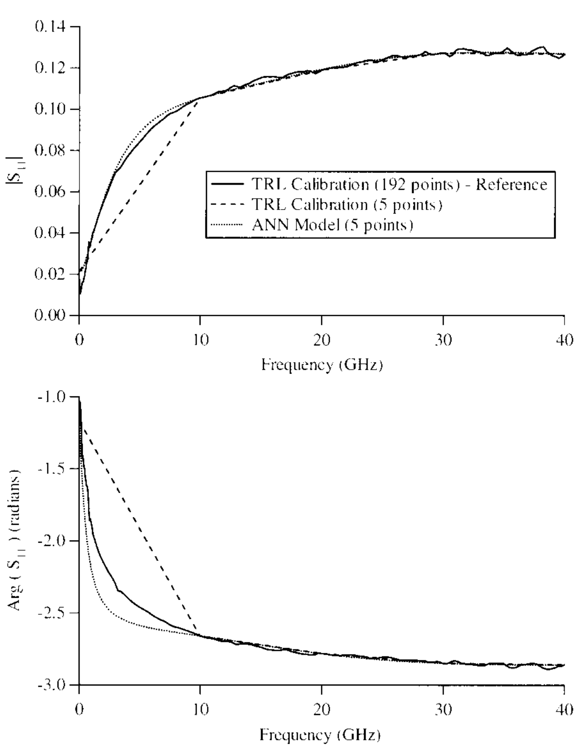

Figure 5. Comparison of magnitude and phase of the reflection coefficients [$|S_{11}|$ and $\arg(S_{11})$] for the load standard using an ANN model trained with five points, linear interpolation with TRL using the same five points, and TRL with 192 points as the reference.

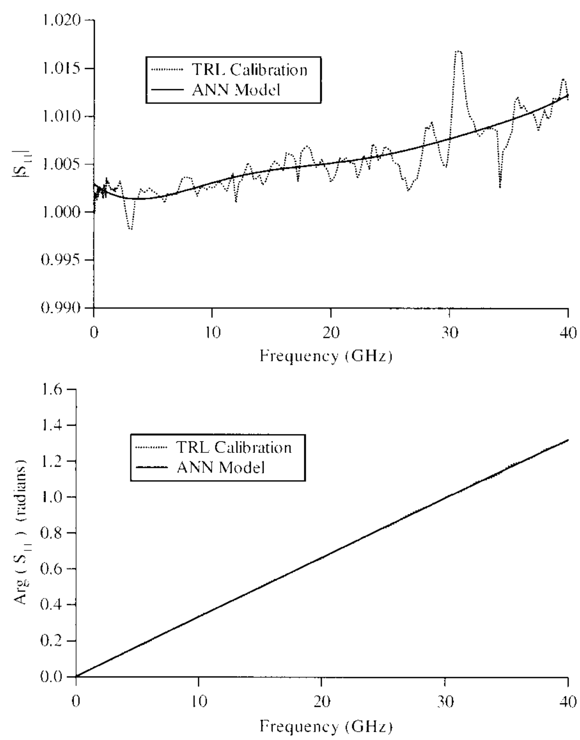

Figure 6. Magnitude and phase of the reflection coefficients [$|S_{11}|$ and $\arg(S_{11})$] for the open standard measured by multiline TRL and ANN modeling.

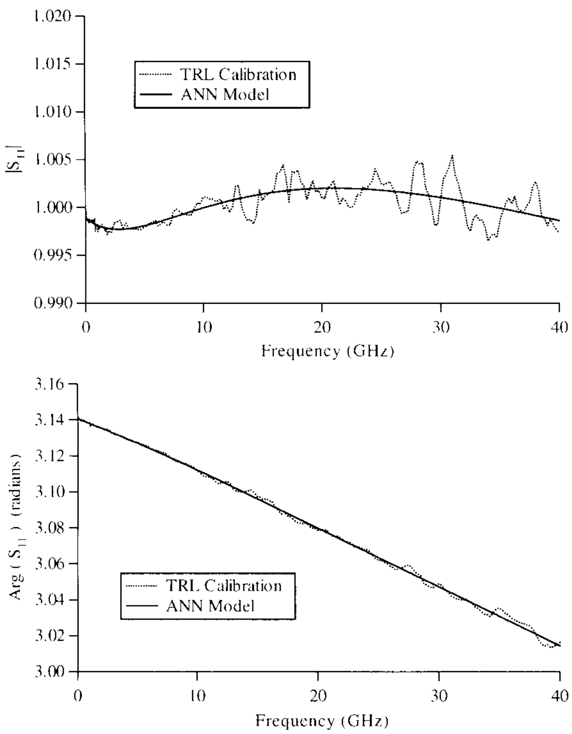

Figure 7. Magnitude and phase of the reflection coefficients [$|S_{11}|$ and $\arg(S_{11})$] for the short standard measured by multiline TRL and ANN modeling.

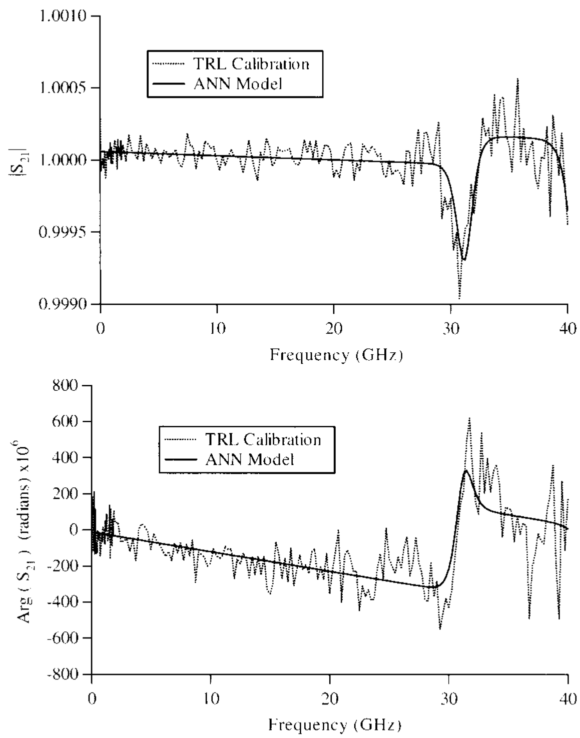

Figure 9. Magnitude and phase of the transmission coefficients [$|S_{21}|$ and $\arg(S_{21})$] for the thru standard measured by multiline TRL and ANN modeling.

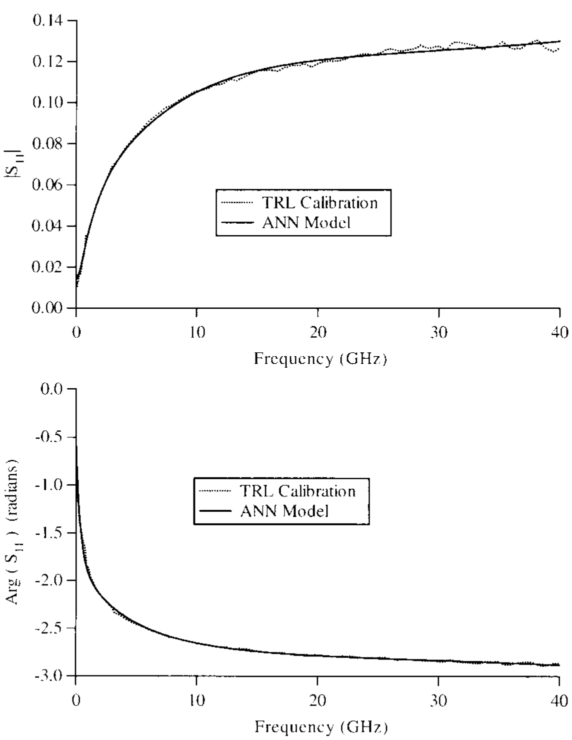

Figure 8. Magnitude and phase of the reflection coefficients [$|S_{11}|$ and $\arg(S_{11})$] for the load standard measured by multiline TRL and ANN modeling.

that ANNs follow general trends, but omit the noise, which is usually desirable in a model. In Figures 6 and 7, the measured magnitudes of the reflection coefficient for the open and short standards are slightly greater than 1, which is not possible for passive devices. This discrepancy can be attributed to random errors in the TRL calibration, which are typically as high as 0.02 at 40 GHz. Fortunately, our measurements never exceed 1 by more than this repeatability error. A similar argument can be made for the transmission coefficients of the thru standard.

B. Calibration Comparison

We performed two OSLT calibrations: one using the calibrated measurement data of the standards, and the other using the ANN models of the standards. We calibrated a 19 mm CPW transmission line using both OSLT calibrations, and compared the results to measurements calibrated directly using the benchmark multiline TRL calibration. Figure 10 compares the magnitude and phase of the scattering parameter data [$|S_{11}|$, $\arg(S_{11})$, $|S_{21}|$, $\arg(S_{21})$] for all three calibrations. The agreement is remarkably good.

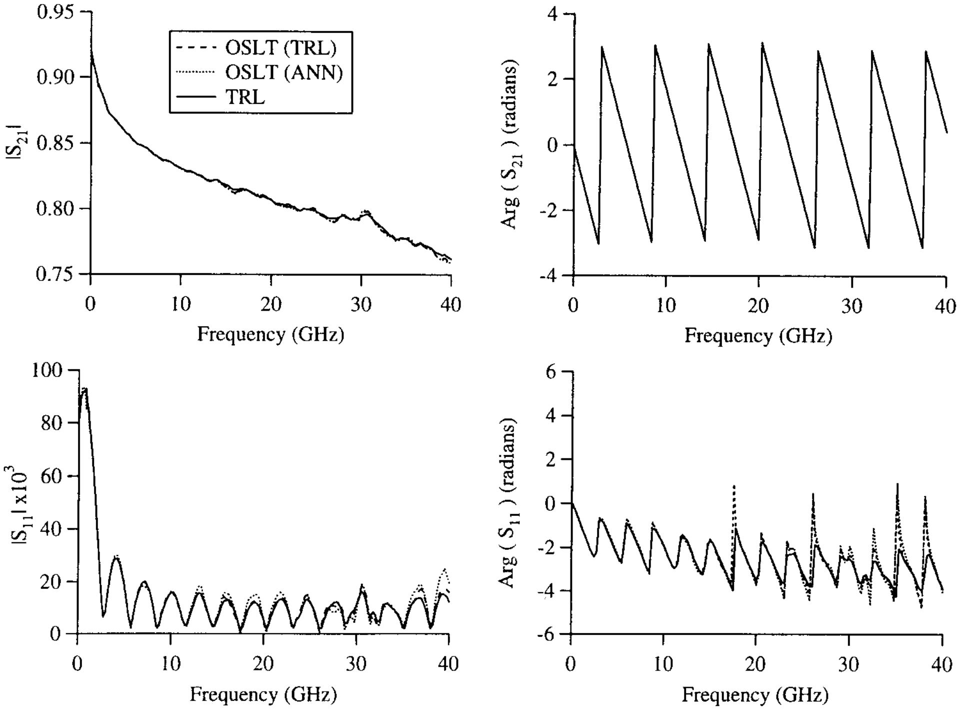

Figure 10. Magnitude and phase of the scattering parameters of a calibrated 19 mm CPW transmission line.

To obtain a more quantitative idea of the differences, we plotted the maximum vector differences of the scattering parameters ($|\Delta S_{ij}|$) for the 19 mm line between the two OSLT calibrations and the multiline TRL calibration. Figure 11 illustrates the differences. Not surprisingly, the OSLT calibration, using the calibrated measurement data, compares better to the multiline TRL calibration since they both make use of the same calibration data. However, the OSLT using the

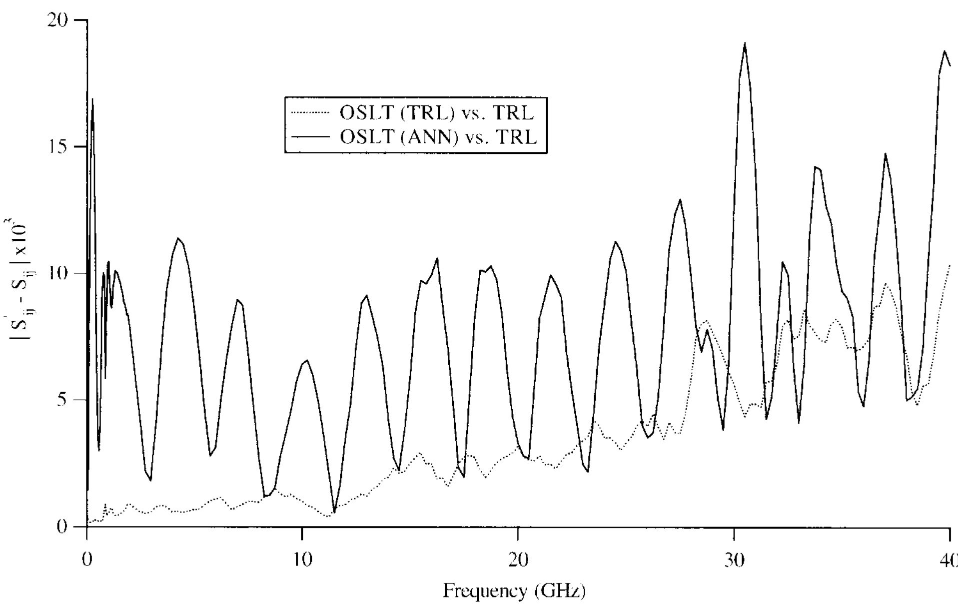

Figure 11. Magnitude of the scattering parameter differences ($|\Delta S_{ij}|$) of a calibrated 19 mm CPW transmission line.

ANN models still compares well with less than a 0.02 difference in magnitude at all frequencies. The difference here does not necessarily mean that the OSLT, using ANN models, is in error. The differences could be due to the presence of noise in the TRL calibration that the ANN models avoided. Regardless of the source of error, a 0.02 difference between two on-wafer calibrations spanning 40 GHz is impressive, considering that the repeatability between two multiline TRL calibrations is usually on the order of 0.015.

IV. CONCLUSIONS

We have successfully applied ANNs to model on-wafer OSLT standards, and have shown that such a calibration compares favorably (less than a 0.02 difference in magnitude) to the benchmark multiline TRL calibration. In modeling these standards, we quantified the training errors and training times as a function of both the number of training points and the number of neurons in the hidden layer. We found that five neurons in the hidden layer of an MLP3 architecture and that fewer than ten training points were sufficient to accurately model our standards.

In practice, ANN-modeled calibration standards can be easily implemented using existing or custom software packages. In our case, we utilized MultiCal, a free program developed by the National Institute of Standards and Technology, to perform our benchmark multiline TRL calibration. The internal software on any commercial network analyzer can also be used if the user has confidence in another calibration method such as single-line TRL or LRM (line-reflect-match). Then, once the OSLT standards are measured, one of a number of ANN programs may be used to model the standards. We used software developed by Zhang et al. [18] to construct our ANN models. Finally, a program that can perform OSLT calibrations using exported ANN models is required. We wrote custom software to perform this task, using the equations found in [1] and [6] to perform the OSLT calibrations.

We have shown that ANN models offer a number of advantages over using calibrated measurement data files or equivalent circuit models, namely, the following.

1. They do not require detailed physical models.
2. Calibration times can be reduced since only a few training points are required to accurately model the standards.
3. ANN model descriptions are much more compact than large measurement data files.
4. ANN models, trained on only a few measurement points, can be much more accurate than direct calibrations, when limited data are available.
5. They are less susceptible to the noise inherent in measured data.

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BIOGRAPHIES

Jeffrey A. Jargon was born in Denver, CO, in 1967. He received the B.S. and M.S. degrees in electrical engineering from the University of Colorado at Boulder, in 1990 and 1996, respectively. He has been with the Radio Frequency Technology Division, National Institute of Standards and Technology (NIST), Boulder, CO, since 1990. His current research interests include calibration techniques for vector network analyzers and passive intermodulation in wireless communications. Mr. Jargon is a member of Tau Beta Pi and Eta Kappa Nu, and is a registered Professional Engineer in the State of Colorado. He is currently pursuing the Ph.D. degree in electrical engineering at the University of Colorado at Boulder.

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Dr. Gupta has been at the University of Colorado since 1983, initially as a visiting professor and later as a professor. Presently, he is also the Associate Director for the NSF I/UCR Center for Advanced Manufacturing and Packaging of Microwave, Optical and Digital Electronics (CAMPmode) at the University of Colorado. Earlier, he had a long stay (since 1969) at the Indian Institute of Technology, Kanpur, where he was a Professor in Electrical Engineering. On leave from IITK, he has been a visiting professor at the University of Waterloo, Canada; Ecole Polytechnique Federale de Lausanne, Switzerland; Technical University of Denmark (Lyngby); Eidgenossische Technische Hochschule, Zurich; and the University of Kansas, Lawrence. From 1971 to 1979, he was the Coordinator for the Phased Array Radar Group of the Advanced Center for Electronics Systems at the Indian Institute of Technology. On sabbatical from the University of Colorado in 1993–94, Dr. Gupta was a visiting professor at the Indian Institute of Science in Bangalore and a Consultant at the Indian Telephone Industries.

Dr. Gupta's current research interests are in the area of computer-aided design techniques for microwave and millimeter-wave integrated circuits and integrated antennas. He is the author or co-author of six books: *Microwave Integrated Circuits* (Wiley Eastern, 1974; Halsted Press of John Wiley, 1974); *Microstrip Line and Slotlines* (Artech House, 1979; revised second edition, 1996); *Microwaves* (Wiley Eastern, 1979; Halsted Press of John Wiley, 1980; Editorial Limusa Mexico, 1983); *CAD of Microwave Circuits* (Artech House, 1981; Chinese Scientific Press, 1986; Radio I Syvaz, 1987); *Microstrip Antenna Design* (Artech House, 1988); and *Analysis and Design of Planar Microwave Components* (IEEE Press, 1994). Also, he has contributed chapters to the *Handbook of Microstrip Antennas* (Peter Peregrinus, 1989); the *Handbook of Microwave and Optical Components*, vol. 1 (John Wiley, 1989); *Microwave Solid State Circuit Design* (John Wiley, 1988); and to *Numerical Techniques for Microwave and Millimeter Wave Passive Structures* (John Wiley, 1989). Dr. Gupta has published over 170 research papers and holds three patents in the microwave area.

Dr. Gupta is a Fellow of the IEEE (Institute of Electrical and Electronics Engineers, USA); a Fellow of the Institution of Electronics and Telecommunication Engineers (India); a Member of URSI (Commission D, USA); and a Member of the Electromagnetics Academy (MIT, USA). He is a member of the ADCOM for the MTT Society of IEEE, a co-chair of the IEEE MTT-S Technical Committee on CAD (MTT-1), a member of the IEEE Technical Committee on Microwave Field Theory (MTT-15), and on the Technical Program Committees for MTT-S International Symposia. He is the founding editor of the *International Journal of Microwave and Millimeter-Wave Computer-Aided Engineering*, published by John Wiley since 1991. He is on the editorial boards of *IEEE*

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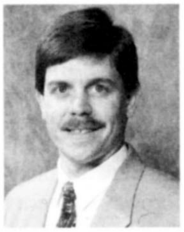

Donald C. DeGroot received the Bachelor's degree in electronics engineering from Andrews University in 1985, and the M.S. and Ph.D. degrees in electrical engineering from Northwestern University in 1990 and 1993, respectively. Currently, he is a Project Leader with the NIST RF Electronics Group, where he develops new electrical characterization techniques for nonlinear devices and networks. His present research activities include the development of broadband instrumentation and calibration techniques for the verification of measurement- and model-based descriptions of nonlinear circuits. He holds a concurrent appointment as a Professor Adjoint of Electrical and Computer Engineering at the University of Colorado at Boulder. Prior to joining the RF Electronics Group, he researched and developed microwave superconducting devices and thin-film measurements as a National Research Council Postdoctoral Associate at NIST, studied the high-frequency properties of novel electronic materials at Northwestern University, and designed high-speed instrumentation at Fermi National Accelerator Laboratory.